DOI 10.15622/ia.22.5.7

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EVALUATION OF SKELETONIZATION TECHNIQUES FOR 2D BINARY IMAGES

Abudalfa S.I. **Evaluation of Skeletonization Techniques for 2D Binary Images.**

Abstract. In the realm of modern image processing, the emphasis often lies on engineering-based approaches rather than scientific solutions to address diverse practical problems. One prevalent task within this domain involves the skeletonization of binary images. Skeletonization is a powerful process for extracting the skeleton of objects located in digital binary images. This process is widely employed for automating many tasks in numerous fields such as pattern recognition, robot vision, animation, and image analysis. The existing skeletonization techniques are mainly based on three approaches: boundary erosion, distance coding, and Voronoi diagram for identifying an approximate skeleton. In this work, we present an empirical evaluation of a set of well-known techniques and report our findings. We specifically deal with computing skeletons in 2d binary images by selecting different approaches and evaluating their effectiveness. Visual evaluation is the primary method used to showcase the performance of selected skeletonization algorithms. Due to the absence of a definitive definition for the "true" skeleton of a digital object, accurately assessing the effectiveness of skeletonization algorithms poses a significant research challenge. The experimental results shown in this work illustrate the performance of the three main approaches in applying skeletonization with respect to different perspectives.

Keywords: image processing, skeletonization techniques, skeleton, 2d binary images.

1. Introduction. The skeleton is a simplified representation of an object that preserves its key topological and geometrical characteristics while being equidistant to its boundaries. Its purpose is to extract a shape feature that represents the general form of an object. The concept of a skeleton was introduced by H. Blum [1] as a result of the Medial Axis Transform (MAT) or Symmetry Axis Transform (SAT), which determines the closest boundary point(s) for each point in an object. An inner point belongs to the skeleton if it has at least two closest boundary points.

The skeleton [2] is much thinner than the original object as it contains far fewer points. It captures local object symmetries and the topological structure of the object while preserving its shape and topology. However, MATs are curves (1D) in a 2D object and surfaces (2D) in a 3D object that are not stable under boundary perturbation, and the same skeleton may belong to different elongated objects.

Skeletons are crucial for object representation in computer graphics and image shape analysis, including bio-medical image analysis and recognition in different fields. Methods based on the computation of an object's skeleton are widely used in pattern recognition and image shape classification, as the skeleton or MAT of the object is an essential descriptor of its shape. Skeletons are used to generate features for determining the similarity measures of various shapes in constructing classifiers.

Various approaches exist for identifying skeletons and they are mainly based on boundary erosion, distance coding, and Voronoi diagram. The primary aim of this work is to implement and evaluate various skeletonization techniques drawn from the literature that embody different approaches to the task.

The remainder of this paper is structured as follows: Section 2 presents a background for this research direction. Section 3 provides a review of relevant studies. Section 4 details the methodology employed to address the research problem. Section 5 analyzes the results obtained from the experiments. Lastly, Section 6 concludes the paper and highlights potential avenues for future research.

2. Background. In this section, brief descriptions are introduced for presenting the approaches and techniques used for applying skeletonization to 2D binary images. The next subsections present the techniques used with the three main approaches of Skeletonization.

2.1. Erosion-Based Skeletonization. This approach of skeletonization can be implemented by using two methods as described in the next subsections.

2.1.1. Morphological-Based Skeletonization. In this method, we use morphological operation [3] to compute object skeletons. The skeleton of image A can be expressed in terms of erosions and openings as shown in Equation (1):

$$S(A) = \bigcup_{k=0}^{K} S_k(A), where\ K = \max\{k | A\Theta kB \neq \emptyset\}, \tag{1}$$

$$S_k(A) = (A\Theta kB) - (A\Theta kB) \circ B,$$

where B is a structuring element, and $(A\Theta kB)$ indicates k successive erosions of A as shown in Equation (2):

$$(A\Theta kB) = ((\dots((A\Theta B)\Theta B)\Theta \dots)\Theta B. \tag{2}$$

From the other side, A (original object) can be reconstructed from these subsets by using Equation (3):

$$A = \cup_{k=0}^{K}(S_k(A) \oplus kB)\ , \tag{3}$$

where $S_k(A) \oplus kB$ denotes k successive dilations of $S_k(A)$ as shown in equation (4):

$$(S_k(A) \oplus kB) = ((\dots((S_k(A) \oplus B) \oplus B) \oplus B) \dots) \oplus B. \tag{4}$$

2.1.2. Thinning-Based Skeletonization. We can use morphological thinning operations [4] to identify the skeleton by iteratively removing pixels on the boundaries of objects and preserving object topology from breaking it into parts as shown in Figure 1.

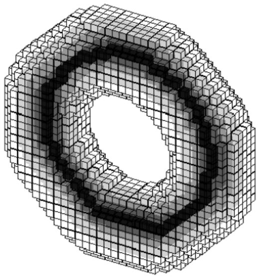


Fig. 1. The darkest voxels belong to the computed skeleton
(Retrieved from http://www.inf.u-szeged.hu/~palagyi/skel/skel.html)

The thinning method is known to possess certain advantageous characteristics. For instance, it helps retain the original shape and topology of an object while positioning the skeleton in the center of the object, resulting in a skeleton that is one pixel/voxel wide. However, it may not always preserve the topology completely, as it may lead to object disconnection, complete object removal, or formation of cavities (i.e., white connected components enclosed by an object).

2.2. Voronoi Diagram-Based Skeletonization. Under this approach, as the density of boundary points (i.e., generating points) tends towards infinity, the associated Voronoi diagram gradually approaches the skeleton [5]. Figure 2 illustrates the idea by showing Voronoi diagram and skeleton for the rectangular object.

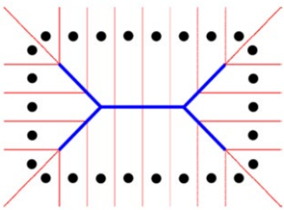


Fig. 2. The skeleton is marked by blue lines
(Retrieved from http://www.inf.u-szeged.hu/~palagyi/skel/skel.html)

By exclusively utilizing pixels located on an object's boundary, this approach proves to be highly efficient for thick objects, with efficiency increasing in proportion to the object's radius, rather than its overall area. However, it may be susceptible to minor defects present on the boundaries (or small holes within the object). Additionally, this approach is capable of analytically determining the topology of the skeleton and can produce output that includes the vertices and edges of the skeleton graph.

2.3. Distance Map-Based Skeletonization. Under this approach, the distance transform [6] assigns a value to each pixel in the binary image B, representing the distance between that pixel and the nearest non-zero pixel of B. The ridges, which refer to local extremes, are subsequently identified as skeletal points. Figure 3 offers a visual depiction of the distance transformation and illustrates the ridges that form part of the skeleton.

a) b)

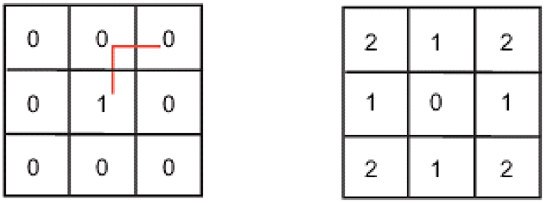
Fig. 3. Distance Map-Based Skeletonization: a) binary image; b) distance map (non-binary image)
(Retrieved from http://www.inf.u-szeged.hu/~palagyi/skel/skel.html)

Numerous distance measures [7] can be used to compute distance maps. The next subsections describe the distance measures that are used in our work. In the last subsection, we introduce a brief description of the Fast Marching algorithm which is used for improving the accuracy of distance map-based skeletonization.

2.3.1. City-Block Distance. This measure is based on 4-neighbor adjacency in calculating distance. Equation 5 illustrates how to calculate the distance in two-dimensional space with respect to two points – (x1,y1) and (x2,y2):

$$|x1 - x2| + |y1 - y2|. \quad (5)$$

Figure 4 shows a simple example of calculating distances between the center and their neighbors by using city-block measure. As illustrated in the figure, the distance which is calculated between the original pixel and its diagonal neighbors (N_D) is 2 while the distance value is 1 for the 4-neighbors (N_4) because this measure is specifically based on 4-neighbor adjacency.

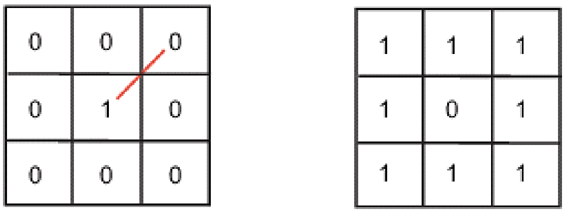


a) b)

Fig. 4. Distance transform using city-block measure: a) image; b) distance transform (Retrieved from https://www.mathworks.com/help/images/distance-transform-of-a-binary-image.html)

2.3.2. Chess-Board Distance. This measure is based on 8-neighbor adjacency for calculating distance by using Equation 6. As illustrated in Figure 5 the distance between the original pixel and its 8-neighbor (N_8) is 1 because this measure based on 8-neighbor adjacency.

$$\max(|x1 - x2|, |y1 - y2|), \quad (6)$$



a) b)

Fig. 5. Distance transform using Chess-Board measure: a) image; b) distance transform (Retrieved from https://www.mathworks.com/help/images/distance-transform-of-a-binary-image.html)

2.3.3. Euclidean Distance. Euclidean distance is a famous distance measure and it is used widely in many applications by using the following Equation 7. Figure 6 shows that N_D took more distance value than N_4 based on the Euclidean distance measure. However, this value is less than 2 which is calculated by using the city-block measure.

$$\sqrt{(x_1 - x_2)^2 + (y_1 - y_{2)}{}^2} \quad (7)$$

0	0	0
0	1	0
0	0	0

a)

1.41	1.0	1.41
1.0	0.0	1.0
1.41	1.0	1.41

b)

Fig. 6. Distance transform using Euclidean measure: a) image; b) distance transform (Retrieved from https://www.mathworks.com/help/images/distance-transform-of-a-binary-image.html)

2.3.4. Quasi-Euclidean Distance. The quasi-Euclidean distance measure is an improved version of the Euclidean measure which is calculated by using Equation 8. The effect of this measure on the neighbor distances is more widely as illustrated in Figure 7:

$$|x_1 - x_2| + (\sqrt{2} - 1)|y_1 - y_2|, |x_1 - x_2| > |y_1 - y_2|, \tag{8}$$

$$(\sqrt{2} - 1)|x_1 - x_2| + |y_1 - y_2|, otherwise.$$

0	0	0	0	0
0	0	0	0	0
0	0	1	0	0
0	0	0	0	0
0	0	0	0	0

a)

2.8	2.4	2.0	2.4	2.8
2.4	1.4	1.0	1.4	2.4
2.0	1.0	0	1.0	2.0
2.4	1.4	1.0	1.4	2.4
2.8	2.4	2.0	2.4	2.8

b)

Fig. 7. Distance transform using the quasi-Euclidean measure: a) image; b) distance transform
(Retrieved from https://www.mathworks.com/help/images/distance-transform-of-a-binary-image.html)

2.3.5. Improving Distance Map Based Skeletonization. The basic algorithm for finding local maximum ridges through computing skeletons is based on comparing N_4 neighbors. In this work, we evaluate also the performance of using N_8 neighbors in detecting the local maximum to increase the accuracy of resulted skeletons. Based on the results of our experiments, we have observed that increasing the number of selected neighbors enhances the performance of distance map-based skeletonization.

2.3.6. Fast Marching Algorithm. The Fast Marching algorithm [8] is a numerical technique that accurately captures the viscosity solution of the Eikonal equation, norm(grad(D))=P. The level set {x \ F(x)=t} represents a front that progressively advances with a speed of P(x). The resultant function D acts as a distance function, and if the velocity P remains constant, it can be viewed as the distance function for a group of initial points. The Fast Marching is very similar to the Dijkstra algorithm [9] that finds the shortest paths on graphs. Therefore, we can use the Fast Marching technique to compute the distance map for a more accurate resulted transformation.

3. Literature Review. We surveyed two main aspects related to skeletonization of 2d binary images in order to conduct experiment work. The first aspect leads us to explore several approaches for evaluating the skeletonization techniques. The second aspect is to evaluate the performance of some selected techniques.

The literature classifies the skeletonization techniques into three main categories based on the implementation view [10]. The first group of skeletonization techniques computes skeletons by detecting ridges in the distance map of the boundary points [11]. The second category is based on calculating the Voronoi diagram generated by the boundary points [12]. While the third group employs a layer-by-layer erosion technique known as thinning [13].

In digital spaces, only an approximation of the "true skeleton" can be extracted. There are two requirements to be complied with: 1) Topological [14] to retain the topology of the original object. 2) Geometrical [15] to force the skeleton to be in the middle of the object and invariance under the most important geometrical transformation including translation, rotation, and scaling.

Skeletonization methods that rely on the distance transform can only retain geometrical properties, whereas those based on thinning can solely preserve topological properties. On the other hand, skeletonization techniques that utilize Voronoi-Skeleton can successfully retain both sets of requirements. Table 1 illustrates a comparison between these three approaches.

Table 1. Comparison between three skeletonization approaches

Approach	Geometrical	Topological
Distance Transform	Yes	No
Voronoi-Skeleton	Yes	Yes
Thinning	No	Yes

While skeletons can be obtained from both 2D and 3D objects [16], our primary focus in this project centers on generating skeletons from 2D images. Consequently, we restrict our analysis solely to skeletonization methods that are applicable to 2D images.

Numerous enhancements have recently been introduced to several existing algorithms presented in the literature, all of which aim to enhance the efficiency of specific tasks by using 2D binary image skeletonization. For example, in paper [17] employ 2D skeleton features with an automated system that overcomes the dimensionality problems with human action recognition. Whereas, in paper [18] the authors present a new framework for extracting skeletons from noisy images and apply this framework to the task of hand gesture recognition.

Some related works evaluated the performance of skeletonization techniques. However, our work is still unique since our evaluation covers different perspectives. In paper [19] the authors present their approach for evaluating the performance of skeletonization methods for document images with rotation states, along with experimental results and discussions. The article discusses the importance of skeletonization in document image analysis and presents various methods used for skeletonization. In the same context, in [20] the authors compare the performance of different image skeletonization methods in biometric security systems.

Skeletonization is widely used for automating in many fields such as biomedical, natural language processing and animation. This high exploitation of skeletonization encouraged us for evaluating the performance of some skeletonization techniques by using images selected from different domains. Thereby, we can claim that our work is unique in comparison with other related works. The next paragraphs present recent works that use skeletonization for conducting many tasks.

In paper [21] the authors discuss the technique of digital skeletonization, which is a widely used method for extracting the structural information of objects in biomedical images. In the same field, in [22] the authors present a study on the analysis of blood vessels in angiogenesis using 3D visualization, skeletonization, and branching analysis techniques.

It is worth mentioning here that skeletonization is widely used for improving the segmentation accuracy of specific areas in biomedical images. For example, in study [23] the authors propose a method for segmenting abdominal arteries from an abdominal computed tomography (CT) volume by leveraging artery skeleton information. Another example was recently revealed with work presented in [24]. The authors propose a new segmentation method based on skeletonization for the cross-sectional optic nerve on magnetic resonance (MR) images.

Skeletonization is also used as a basic approach for action recognition [25]. For example, in study [26] the authors extract skeletal data for utilizing a human tracking. Whereas, in [27] the authors present a method based on skeletonization for recognizing the campus violence. In the same context, in [28] the authors extract the skeleton of the person in the video as a first step for developing a multi-speed transformer network that improves the performance of action recognition. In paper [29] the authors employ as well skeletonization for recognizing human gait gender. Similarly, study [30] present a hybrid network for improving the performance of skeleton-based action recognition.

Additionally, there are a lot of uses for skeletonization with natural language processing. For example, study [31] present a model that employs skeletonization for generating stories in a coherent manner. Whereas, in [32] the authors propose a skeleton Filter for improving the performance of skeletonization in noisy text images.

The skeletonization is widely used as well for detecting text in images and segmenting the resulting text into words and characters. Therefore, the skeletonization is sufficiently used for developing optical character recognition (OCR) systems [33] with natural languages. For example, in [34] the authors present a technique for analyzing the Arabic text documents. The authors evaluated the performance of their work on a set of text images selected from the King Fahd University of Petroleum and Minerals (KFUPM) handwritten Arabic text (KHATT) database.

In the same context, study [35] presents a segmentation algorithm for handwritten Arabic word recognition. Their presented algorithm provides a description of skeleton points including their coordinates, types, and the number of neighboring points in the 8-neighborhood. This enables the extraction of representative primitives of characteristic points, which are utilized in the segmentation phase.

It is worth mentioning here that our study does not deal with the skeletonization in terms of computational efficiency. Skeletonization techniques can be categorized into two types: sequential methods, such as those described in references [36, 37], and parallel methods, as described in references [38, 39, 40].

Of course, employing parallel methods will reduce computational time in comparison with sequential methods. However, certain types of skeletons can only be calculated using sequential algorithms, while other types can only be obtained through parallel algorithms. Whereas, for many types of skeletons, both sequential and parallel algorithms can be used, especially when working with digital structures.

With sequential algorithms, there is a risk of producing different skeletons depending on the order in which the elements are processed. In contrast, parallel algorithms are generally faster, but maintaining topology preservation can be a challenging task.

To understand the efficacy of employing methods with skeletonization techniques, the reader may refer to the recent work presented in [41]. The authors present a fully parallel thinning algorithm through a thorough examination of the popular Zhang-Suen (ZS) series algorithms and the one-pass thinning algorithm (OPTA) series algorithms. In terms of handling boundary noise, their algorithm has demonstrated greater robustness than the OPTA-series algorithms. Furthermore, it exhibits a faster thinning speed compared to the ZS-series algorithms.

Based on our knowledge, modern skeletonization methods [42, 43] have often been developed and tailored to address specific domains, limiting their applicability across diverse domains. Therefore, there are still some challenges that should be addressed in this research direction.

4. Methodology. In this section, we describe the methodology used for conducting the empirical analysis. The main objective of this research work is to compute approximate skeletons for 2D objects using different techniques. We collected binary images that contain different 2D objects to extract skeletons. We selected images from different domains to make our empirical analysis unique. Thereby, this work shows different perspectives for analyzing the selected models. Some of these images are cropped from the KHATT database to compute also skeletons for characters. In order to achieve this objective the following tools and programs are used for conducting our experiments:

– Matlab: is used for image processing and programming purposes.
– C++ compiler: is used to compile a code that is related to building Voronoi diagram in reasonable time-consuming.
– We use qhull tool[1] for computing voronoi diagram.
– Using Toolbox entitled Fast Marching[2] for implementing the Fast Marching algorithm.

In this work, we use visual evaluation for showing the performance of the selected skeletonization algorithms. The lack of a clear definition for the "true" skeleton of a digital object presents a significant research challenge when it comes to evaluating the performance of skeletonization algorithms [44]. Therefore, visual evaluation is still the most traded method used for assessing the performance of different skeletonization algorithms. There are some attempts made by researchers for presenting a quantitative assessment of skeletonization algorithms [45]. However, the resulting measures are used for custom domains and do not fit our work.

[1] http://www.qhull.org/

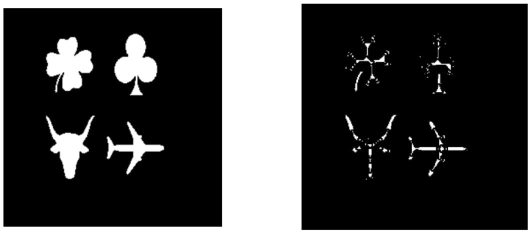
[2] https://www.mathworks.com/matlabcentral/fileexchange/6110-toolbox-fast-marching

5. Experiment Results. This section presents all results of our experiments conducted to evaluate the selected skeletonization techniques. The next subsections show the results with sufficient analysis.

5.1. Morphological-Based Skeletonization. Figure 8 shows the results of applying 7 iterations of erosion and opening morphological operations to compute skeletons. Matrix B illustrates the structural element that used in this experiment. We selected circular shape structural elements to increase the accuracy of computing the skeleton based on finding MAT.

We can note from the figure that the results are not accurate and the skeleton width is more than one pixel whereas it is not connected. Thus, we can conclude that using morphological operations is not an accurate technique for computing skeletons.

$$B = \begin{matrix} 0 & 1 & 1 & 1 & 0 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 0 & 1 & 1 & 1 & 0 \end{matrix}$$



a) b) c)

Fig. 8. Morphological Based Skeletonization: a) Structural Element; b) Original Image A (256x256); c) Skeleton

Figure 9 shows the results of applying dilation morphological operations to reconstruct the object from the skeleton. The figure also shows the accuracy of the reconstructed objects by subtracting the reconstructed image from the original image. We can conclude that this reconstruction technique generated interesting results, but it is not good enough to reconstruct the original shape of objects.

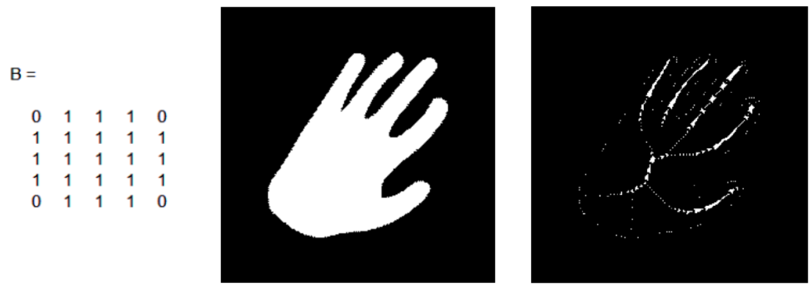
$$B = \begin{matrix} 0 & 1 & 1 & 1 & 0 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 0 & 1 & 1 & 1 & 0 \end{matrix}$$

a) b) c)

Fig. 9. Reconstruction from Morphological Based Skeletonization: a) Structural Element; b) Partial Reconstruction; c) Difference Between Original and Partial Reconstruction

Figure 10 shows the results of computing the skeleton by applying 23 iterations of erosion and opening morphological operations to a large object (hand shape). We can clearly note that the result is not accurate, but the interesting observation is shown in Figure 11 which illustrates that a very small portion of the hand object (without even identifying the object shape) is reconstructed using dilation morphological operations.

Thus, we can conclude that using large objects is not suitable with this technique because the size of the structural element is very small in comparison with the object size. This means that the morphological-based Skeletonization technique is sensitive to the size of the structural element.



a) b) c)

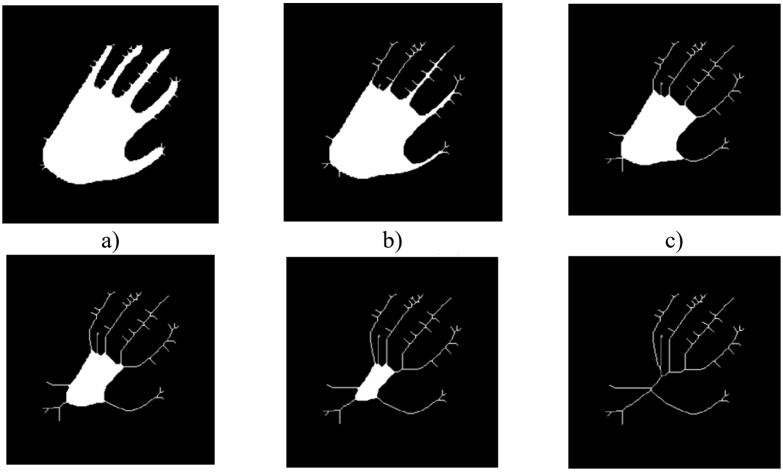
Fig. 10. Morphological-Based Skeletonization (Large Object): a) Structural Element; b) Original Image A (256x256); c) Skeleton

a) b) c)

Fig. 11. Reconstruction from Morphological-Based Skeletonization: a) Structural Element; b) Partial Reconstruction; c) Difference Between Original and Partial Reconstruction

5.2. Thinning-Based Skeletonization. Figure 12 shows the results of using thinning morphological operations to compute the skeleton with using different numbers of thinning operations (k). In this experiment, we used the same image illustrated in Figure 10. We can note that this technique generates very accurate results and preserves the object's shape.

Figure 13 shows the results of applying this technique on medical images (blood vessels) whereas Figure 14 and Figure 15 show the results of applying this technique on cropped images selected from the KHATT dataset for computing skeletons of text.



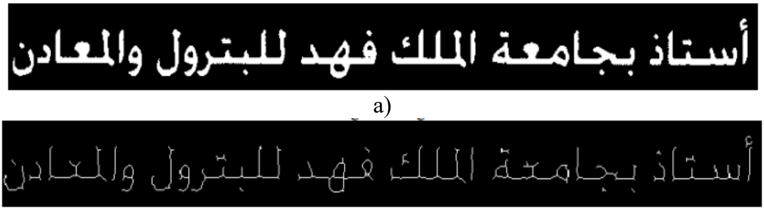
a) b) c)

d) e) f)

Fig. 12. Thinning-Based Skeletonization: a) Skeletonization with k=5; b) Skeletonization with k=10; c) Skeletonization with k=20; d) Skeletonization with k=30; e) Skeletonization with k=40; f) Skeletonization with k>50

a) b)

Fig. 13. Thinning-Based Skeletonization: a) Original Image; b) Skeleton



b)

Fig. 14. Thinning-Based Skeletonization: a) Original Image; b) Skeleton

a) b)

Fig. 15. Thinning Based Skeletonization: a) Original Image; b) Skeleton

5.3. Voronoi Diagram-Based Skeletonization. Figure 16 shows a sample result of applying Voronoi diagram-based skeletonization to an image that includes a hand object. When we compare the results of this technique with the results of morphological and thinning-based skeletonization, it is worth noting that this technique outperforms morphological techniques in terms of achieving better results. However, it is not better than thinning-based skeletonization.

a) b)

Fig. 16. Voronoi Diagram Based Skeletonization: a) Original Image; b) Skeleton

5.4. Distance Map-Based Skeletonization. Figure 17 shows the results of applying distance map-based skeletonization by using four distance measures [46]. We can note that using city-block distance performs the best results since it generates the most accurate skeleton with preserving object shape. However, this technique is not better than thinning-based skeletonization nor Voronoi diagram-based skeletonization since the skeleton shape is not connected. We can also say that it is better than morphological-based technique.

5.5. Improved Distance Map-Based Skeletonization. We tried to do some improvements to the distance map-based technique by applying alternative methods for detecting local maximum values from the distance map when computing the skeleton. The detail of this method is presented in Section 2.3.5.

Figure 18 shows the results of our suggested improvement. We can note that the results are less sensitive in comparison with the original algorithm of skeletonization which is based on distance measure.

We can also note that the best results are provided with the skeleton that is computed by using chess-board distance followed by removing many useless branches from the first version of the skeleton shape. This result reveals that our work may be extended by evaluating the performance of applying more distance measures and employing suitable modifications that provide an accurate form of skeleton shape.

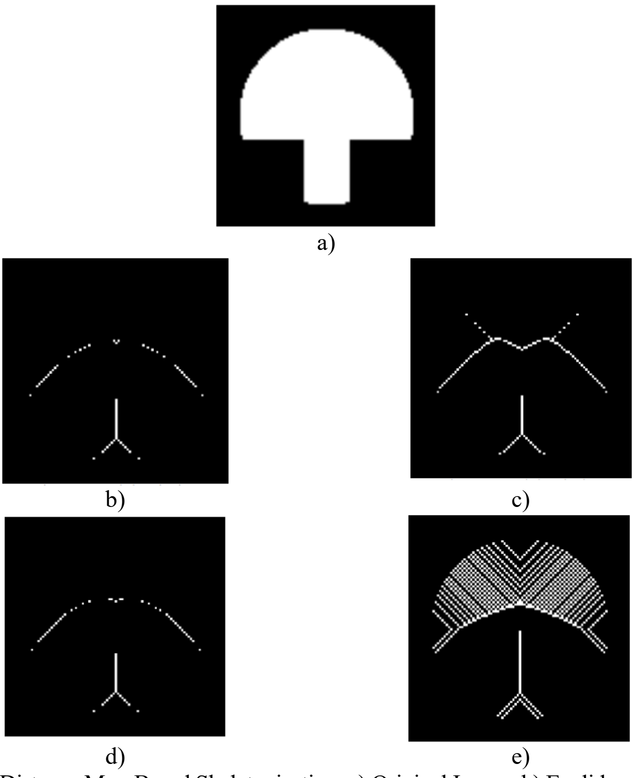


Fig. 17. Distance Map-Based Skeletonization: a) Original Image; b) Euclidean Distance; c) City-Block Distance; d) Quasi-Euclidean Distance e) Chess-Board Distance

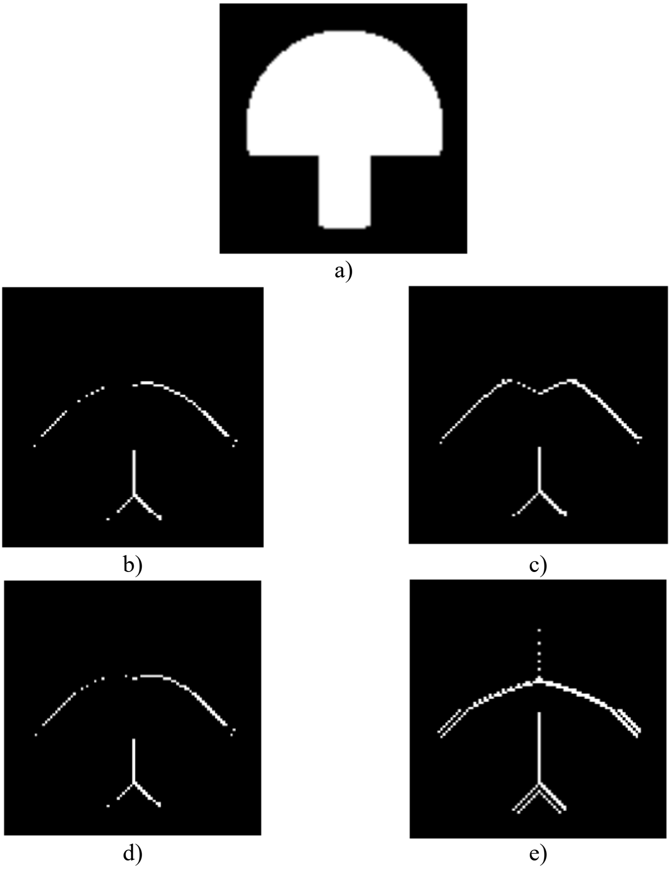
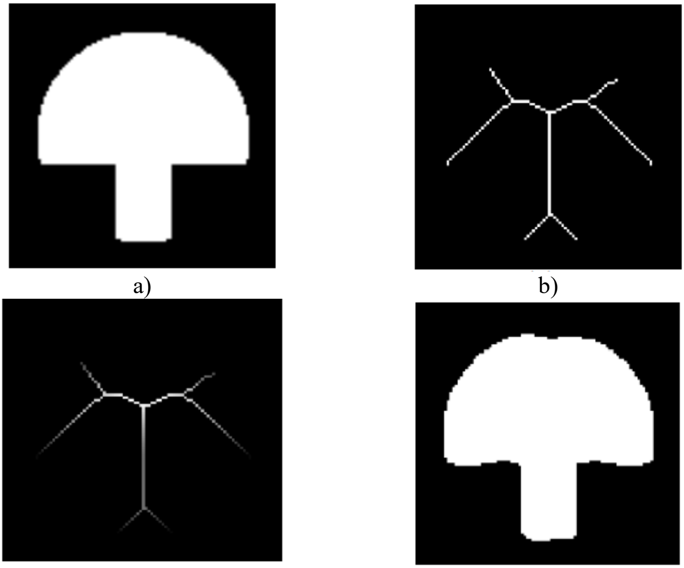


Fig. 18. Improved Distance Map-Based Skeletonization: a) Original Image; b) Euclidean Distance; c) City-Block Distance; d) Quasi-Euclidean Distance e) Chess-Board Distance

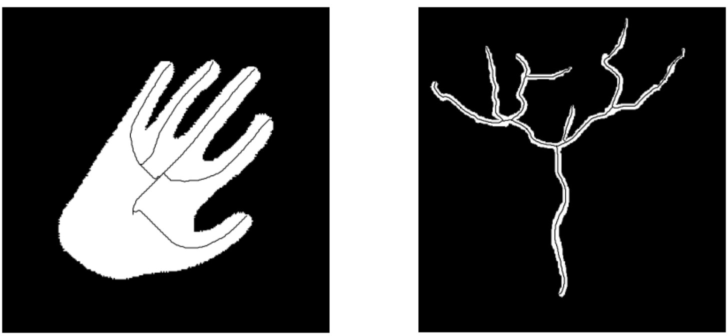
We can also inversely employ the distance transformation technique to reconstruct approximated shapes for the original object. Figure 19 shows the results of using this technique to reconstruct the approximated shape of a mushroom object. We can note from the figure that this technique is good enough for computing the approximate shape of the original object. However, we cannot claim that the reconstructed shape is the original object since the same skeleton may belong to different objects.



a) b) c) d)

Fig. 19. Object Reconstruction using Distance Transform: a) Original Image; b) Skelton; c) Skelton + Distance Transform; d) Inverse Distance Transform

5.6. Distance Map-Based Skeletonization using the Fast Marching Algorithm. Figure 20 shows the results of computing a very accurate skeleton by using the fast marching algorithm. We can note that this technique is robust and computes skeletons that preserve the topological and geometrical requirements of objects.



a) b)

Fig. 20. Distance Map-Based Skeletonization using Fast Marching: a) Extracted Skeleton; b) Extracted Skeleton

6. Conclusion and Future Work. In this work, we present a comparative study to evaluate three categories of skeletonization techniques: boundary erosion, distance coding, and Voronoi diagram. Based on our experiment results, thining-based skeletonization performs the best results.

In digital spaces, only an approximation of the "true skeleton" can be extracted. Thus, depending on the excepted outcomes, the developed experiment can compute skeletons that are approximate to the optimal skeletons in 2d binary images.

In this work, we evaluate the effectiveness and performance of skeletonization techniques by presenting visualization techniques for image skeletonization. We also visualize the efficiency of reconstructing objects from skeletons.

This work can be extended in different directions. Exploring enhanced approaches for distance map-based skeletonization would be an intriguing direction to pursue. Employing more distance measures may reveal competitive results in detecting skeletons. Additionally, evaluating the performance of merging more than one skeletonization technique may provide competitive performance and this direction should be explored from numerous perspectives.

Another promising approach would be also an intriguing direction to pursue based on converting a binary image to grayscale by summing pixels within a square mask. Thereby, optimal halftone image approximations can be calculated based on standard deviation. This approach may potentially result in a highlighted skeleton effect and may be used for evaluating the performance of skeletonization techniques.

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УДК 006.72 **DOI** 10.15622/ia.22.5.7

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ОЦЕНКА МЕТОДОВ СКЕЛЕТИЗАЦИИ ДВУМЕРНЫХ БИНАРНЫХ ИЗОБРАЖЕНИЙ

Абудальфа Ш.И. **Оценка методов скелетизации двумерных бинарных изображений.**

Аннотация. В сфере современной обработки изображений упор часто делается на инженерные подходы, а не на научные решения разнообразных практических задач. Одна из распространенных задач в этой области включает скелетирование бинарных изображений. Скелетонизация — это мощный процесс извлечения скелета объектов, находящихся в цифровом бинарном изображении. Этот процесс широко используется для автоматизации многих задач в различных областях, таких как распознавание образов, техническое зрение, анимация и анализ изображений. Существующие методы скелетизации в принципе основаны на трех подходах: эрозии границ, дистанционном кодировании и диаграмме Вороного для идентификации приблизительного скелета. В работе представлены результаты эмпирического оценивания набора хорошо известных методов. Затем выполнен расчет скелетов в двумерном бинарном изображении с выбором различных подходов и оценкой их эффективности. Визуальная оценка – это основной метод, используемый для демонстрации производительности выбранных алгоритмов скелетирования. Из-за отсутствия окончательного определения «истинного» скелета цифрового объекта точная оценка эффективности алгоритмов скелетирования представляет собой серьезную исследовательскую задачу. Были попытки проведения количественной оценки, однако применяемые меры обычно адаптировали для конкретных областей. Экспериментальные результаты, показанные в этой работе, иллюстрируют эффективность трех основных подходов к скелетизации изображений в различных перспективных приложениях.

Ключевые слова: обработка изображений, техники скелетирования, скелет, двумерные бинарные изображения.

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